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Predicting the Ground Water level with Artificial Neural Network: a case Study of Talar Watershed in Ghaemshahr, Iran

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ABSTRACT

Considering these conditions and lack of water resource, the correct management to better use of groundwater resources has a great importance. On one side, this accurate management requires very high care level of these resources using the new computer facilities in this field such as artificial neural networks (ANNs). The main purpose in this study is to obtain the best composition of these inputs to predict the Ground Water Level (GWL) of the next month and then to determine the degree of each of the inputs on the degree of GWL. In this research 156 series of data for the purpose of education and 50 series of data were used for the purpose of web test. Using the input model including GWL, rainfall and evaporation, the model was able to predict GWL of the next month with the suitable accuracy of (R2=0.9018). Finally, by doing the sensitivity analysis, it was clear that the GWL, rainfall and evaporation input parameters have the greatest effect on the next month GWL in Talar watershed respectively.

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INTRODUCTION

Underground waters include a noticeable percentage of active waters in the hydrology circle. These resources, due to being fresh, having fixed chemical compositions, being less polluted and having fixed temperature have more importance than other water resources [1]. For this reason, underground waters are of the most important resources of water providing for consumption, agriculture and industry. The country of Iran, considering the classification of the United Nations, due to being located in the dry, semi-dry and little rainfall receiving area, is one of the countries with little water supply, and will be in the state of sever water shortage. Considering these conditions and shortage of surface water resources, underground water resources are the important supply for water consumption in Iran [2].

Correct management to better use of underground water supplies requires prediction with the high accuracy on these Ground Water Level (GWL) resources. Considering the importance of the issue of predicting, the use of present new computer facilities is necessary at this ANNs level. It is obvious these days that the Artificial Neural Networks, as the black box models in this field, are the useful accepted tools for modeling in complex and non-linier situations without knowing the physical relations of ANNs. Between the input and output parameters, they model the intended procedure.

In recent years, several hydrologic studies were done through ANNs such as predicting [7, 8, 9] discharge river, predicting sediment [10, 11, 12], simulating the process of rainfall-flowing water [13, 14], modeling water quality [15, 16] and predicting the quality and quantity of underground water [17, 18, 19].

The main objective of this research is to obtain the best composition of all the inputs for the prediction of GWL, and then identify the effect of each of the inputs on the level of GWL. In the next section the article related to the area under study is described and the input parameters are introduced. In section 3, a short introduction of ANNs and applied performance criteria are presented. In section 4, the modeling procedure and its results are presented and finally, in section 5, the general results of this research are dealt with.

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Study area and data sets:

Talar River is located in the city of Ghaemshahr in the country of Iran. The length of this river is 150 kilometers which pours into the Caspian Sea. Due to the area being mountainous, in a large area of the heights in the cold season, the fall is in the form of snow. Talar basin includes 4 cities and tens of villages in which 400000 people reside.

To do this research, the statistics and information of Mazandaran province regional water which are extracted from different stations of Talar basin are used together with the information of Roudposht well GWL. The input data to the web is displayed in table 1 with their statistical characteristics and features at the two levels of education and test [20]. To stop the surprise of the model in the test level, the variables intervals, at the test level, should be a subordinate of their intervals at the education level. This subject, as it is observed in table 1, is included in this research.

Table 1: Statistical characteristics of the data in training and testing stages.

Variable	Train				Test			
	Min	Max	Average	Variance	Min	Max	Average	Variance
GWL(m)	6.20	11.85	9.25	1.32	6.97	12.35	9.84	1.87
Rainfall (mm)	5.51	229.67	68.67	1609.37	5.57	156.47	66.86	1417.57
Precipitation (mm)	12.20	176.43	75.83	1899.85	19.90	171.80	84.10	1830.90

MATERIALS AND METHODS

ANNs is one of the subjects that is used a lot in modeling, predicting, predicting, grading and … with a great volume of data. The base of this method is human brain structure which is designed based on the performance type of brain, obtaining information, processing it and finally, producing an outcome [19].

In this research study, to predict the GWL of Talar watershed, a three layer multilayer perceptron was used. MLP is of the types of ANNs the educational algorithm of which is in the observatory form [20]. The three-layer MLP is able to estimate a complex nonlinear subordinate with a suitable accuracy through choosing better architecture and try and error method [21].

Considering the vast domain of the data under use in this research, to normalize the data in the range of -1 to 1, the following relation is used.

$$X_n = [(\frac{X - X_{Min}}{X_{Max} - X_{Min}}) * 2] - 1 \tag{1}$$

Where X and X_n are the raw and normalized data and X_{min} and X_{max} are the minimum and the maximum of the raw data amounts.

The accuracy of prediction is analyzed by performance criteria. The following four performance criteria are used in this research:

$$R^2 = 1 - \frac{\sum_{i=l}^{n}(obs - forc)^2}{\sum_{i=1}^{n}(obs - \overline{obs})^2} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=l}^{N}(obs - forc)^2}{N}} \tag{3}$$

$$MAPE = \frac{100}{N} * \sum \frac{|Obs - forc|}{Obs} \tag{4}$$

$$SDE = \sqrt{\frac{\sum_{i=l}^{N}\left[\frac{|obs - forc|}{\overline{obs}} - \frac{MAPE}{100}\right]^2}{N}} \tag{5}$$

Where obs is the observable flow amount, forc is the degree of predicted flow by the model, $\bar{obs}$ is the mean of obses and N is the number of data at the test stage.

If the amount of the Coefficient of Determination (R^2) is more closer to one, it shows the closeness of the observed and predicted amounts to each other. The performance criteria of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Standard Deviation Error (SDE), the less their performance level, and closer to zero, the better it shows the better performance of MLP [24].

RESULTS AND DISCUSSION

In this research, information from the years 1995 to 2013 on Talar watershed including 206 series of data was used. 50 of the data series were randomly selected for the web test and the rest for the web education. To predict the next month GWL of Talar watershed four input models were used. These input models are presented with accuracy evaluation results at the testing level in Table 2.

Table 2: Model input models and their accuracy evaluation results at the testing level.

Input Pattern	GWL	Precipitation	Rainfall	SDE	MAPE	RMSE	R^2
1	√			0.0426	4.9631	0.6296	0.8004
2	√	√		0.0342	4.1352	0.5028	0.8691
3	√		√	0.0357	4.1577	0.5166	0.8608
4	√	√	√	0.0293	3.4798	0.4377	0.9018

By comparing the performance criteria of input models of 1 with 2 and 1 with 3 the noticeable effect of adding evaporation and rainfall to the input of GWL of the current month is observed. This subject, considering the hydrologic effect of evaporation and rainfall on the level of GWL of the next month was predictable. Also, with the comparison of the performance criteria of input models of 4 with 2 and 4 with 3 the necessity of using all of the effective parameters on the degree of GWL as the input model is determined.

Considering that the input model number 4 is selected as the best and most complete one, after obtaining the best web of this input model and determining its weights, the effect percentage of every input parameter on the next month GWL is obtained through the Garson method which is shown in table 3 [25]. As it can be seen, the current month GWL has the greatest effect on next month GWL and the amount of rainfall and evaporation is almost equal.

Table 3: the effect percentage of every input parameter on the next month GWL amount.

Input parameters	GWL	Evaporation	Rainfall
Effect percentage	60.69	17.99	21.32

To better evaluate the performance of model with input model of 4, the scatter plot of the predicted GWL is observed in front of GWL and is drawn in figure 1. As it can be observed most of the points are close to the perfect line, and only some points are out of the 90% accuracy boundary which shows the closeness of predicted amounts with the observed one.

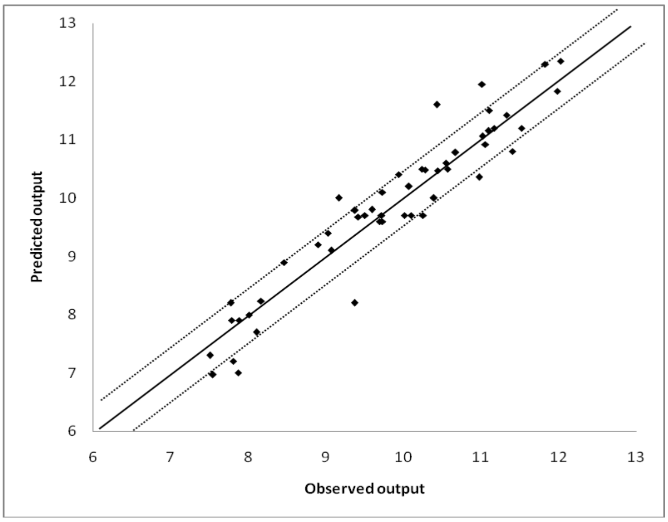

Fig. 1: The distribution curve of the predicted GWL against the observed one with the input model 4 at the test level.

Conclusion:

In underground water resources management plans and programming such as best exploitation of these resources, we need GWL prediction. In this paper, the ANNs are used in predicting the monthly GWL of Roudposht well in Talar watershed the results of which showed that they can be used as accurate and adaptable tools to the physics of the issue. It is shown in this research study that lack of each of the effective parameters in the input pattern of the model decreases its practicality. Finally, it was found through the analysis that the GWL, rainfall and evaporation parameters had the greatest effects on the next month GWL in Talar watershed respectively.

REFERENCES

[1] Mohsenifar, N., N. Mohsenifar, K. Mohsenifar, 2011. Using Artificial Neural Network (ANN) for Estimating Rainfall Relationship with River Pollution, Advances in Environmental Biology, 5(6): 1202-1208.

[2] Fuladipanah, M., E. Sangi, 2013. Neural Network for Estimation of Scour Hole Dimensions Downstream of Siphon Spillway, Advances in Environmental Biology, 7(13): 4254-4264.

[3] World Water Assessment Program, 2003. “The United Nations World Water Development Report 1” Water for People Water for Life. UNESCO, Paris and Berghahn Books, pp: 575.

[4] United Nations, 1997. “Sustainable development of Water Resources in Asia and the Pacific” An overview.

[5] Xi, Z., Y. Zhang, C. Zhu, 2012. “Application of PSO-Neural Network Model in Prediction of Groundwater Level in Handan City” Advances in information Sciences and Service Sciences, 4(6): 177–183.

[6] Adeloye, A.J., R. Rustum, 2012. “Self-organising map rainfall-runoff multivariate modelling for runoff reconstruction in inadequately gauged basins” Hydrology Research, 43(5): 603–617.

[7] He, Z., X. Wen, H. Liu, J. Du, 2014. “A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region” Journal of Hydrology, 509: 379–386.

[8] Huo, Z., S. Feng, S. Kang, G. Huang, F. Wang, P. Guo, 2012. “Integrated neural networks for monthly river flow estimation in arid inland basin of Northwest China” Journal of Hydrology, (420-421): 159–170.

[9] Piotrowski, A.P., J.J. Napiorkowski, 2011. “Optimizing neural networks for river flow forecasting – Evolutionary Computation methods versus the Levenberg–Marquardt approach” Journal of Hydrology, 407(1-4): 12–27.

[10] Rajaee, T., 2011. “Wavelet and ANN combination model for prediction of daily suspended sediment load in rivers” Science of The Total Environment, 409(15): 2917–2928.

[11] Rajaee, T., S.A. Mirbagheri, M. Zounemat-Kermani, V. Nourani, 2009. “Daily suspended sediment concentration simulation using ANN and neuro-fuzzy models” Science of The Total Environment, 407(17): 4916–4927.

[12] Lafdani, K., E. Moghaddam, A. Nia, A. Ahmadi, 2013. “Daily suspended sediment load prediction using artificial neural networks and support vector machines” Journal of Hydrology, 478: 50–62.

[13] Tokar, A.S., P.A. Johnson, 1999. “Rainfall–runoff modelling using artificial neural networks” Journal of Hydrologic Engineering, 4(3): 232–239.

[14] Sedki, A., D. Ouazar, EI.E. Mazoudi, 2009. “Evolving neural network using real coded genetic algorithm for daily rainfall–runoff forecasting” Expert Systems with Applications, 36: 4523–4527.

[15] Khalil, B., T.B.M.J. Ouarda, A. St-Hilaire, 2011. “Estimation of water quality characteristics at ungauged sites using artificial neural networks and canonical correlation analysis” Journal of Hydrology, 405(3-4): 277–287.

[16] Schleiter, I.M., D. Borchardt, R. Wagner, T. Dapper, K.D. Schmidt, H.H. Schmidt, H. Werner, 1999. “Modelling water quality, bioindication and population dynamics in lotic ecosystems using neural networks” Ecological Modelling, 120(2-3): 271–286.

[17] Yoon, H., S.C. Jun, Y. Hyun, G.O. Bae, K.K. Lee, 2011. “A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer” Journal of Hydrology, 396(1-2): 128–138.

[18] Banerjee, P., V.S. Singh, K. Chatttopadhyay, P.C. Chandra, B. Singh, 2011. “Artificial neural network model as a potential alternative for groundwater salinity forecasting” Journal of Hydrology, 398(3-4): 212–220.

[19] Mohanty, S., M.K. Jha, A. Kumar, D.K. Panda, 2013. “Comparative evaluation of numerical model and artificial neural network for simulating groundwater flow in Kathajodi–Surua Inter-basin of Odisha, India” Journal of Hydrology, 495: 38-51.

[20] MRWO, 2012. "Statistical report of Talar River. Mazandaran regional water organization, Studies of examining water resource affairs, Mazandaran, Iran".
[21] Khashei, M., A.Z. Hamadani, M. Bijari, 2012. "A novel hybrid classification model of artificial neural networks and multiple linear regression models" Expert Systems with Applications, 39: 2606–2620.
[22] Islam, A.S., 2010. "Improving flood forecasting in Bangladesh using an artificial neural network" Journal of hydro informatics, 12(3): 351–364.
[23] Talebizadeh, M., A. Moridnejad, 2011. "Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models" Expert Systems with Applications, 38: 4126–4135.
[24] Nash, J.E., J. Sutcliffe, 1970. "River flow forecasting through conceptual models" Journal of Hydrology, 10(3): 282–290.
[25] Garson, G.D., 1991. "Interpreting neural-networks connection weight", AI Expert, 6(7): 47–51.